Impact of Counties' Political Affiliation on COVID-19 Case, Death, and Vaccination Rates

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Abstract

While it is intuitive to expect a causal relationship between a United States county's political affiliation and policy decisions, it is not immediately obvious if the county's status of Republican or Democrat alone impacts medical or behavioral outcomes such as COVID-19 case rates, death rates, and vaccination rates. This paper employs a sharp regression discontinuity design to determine if there is a significant difference in these three outcomes between counties that are "just Republican" or "just Democrat," ceteris paribus, as determined by the popular vote of the 2016 United States Presidential election. The results indicate no significant difference in case, death, or vaccination rates between counties transitioning from a slight Democratic majority to a slight Republican majority. This model can be employed in future research to answer questions such as the impact of face covering policies on COVID-19 vaccination rates.

Keywords: COVID-19, politics, regression discontinuity design, causality

1. Introduction

The United States of America is primarily a two-party political system. Although the U.S. Constitution made no specific provisions to restrict the system to two parties, the Republican and Democratic parties have governed for decades. Additional parties—such as Whig, Federalist, Libertarian, Green, Constitution, and Independent—have emerged over the years, but their popularities remain relatively low. Two of the three colors on the American flag represent the two primary parties—red for the Republicans and blue for the Democrats. When red and blue mix, purple is created—hence the phrase *politically purple*, commonly used to describe those who identify as Independent.

Every four years, the United States conducts a presidential election. While the nation's popular vote does not determine the winning candidate, the winner of each state's popular vote will be the candidate who receives the state's Electoral College votes. The first candidate to receive 270 electoral votes wins the presidency. Therefore, states are commonly characterized as "red" or "blue" depending on the state's track record of its popular vote leaning Republican or Democrat. Furthermore, each county in the United States can similarly be characterized as "red" or "blue." This political structure raises the question of whether or not a county's "red" or "blue" status has any exogenous effect on county-level outcomes.

This paper employs a regression discontinuity design (RDD) to study the impact of a county's political affiliation on three county-level outcomes: COVID-19 case rates, death rates, and vaccination rates. The most robust specifications of this paper's RDD reveal that being a "red" or "blue" county, in and of itself, had no significant impact on COVID-19 death rates, case rates, or vaccination rates. This paper will first provide context for the research question. Next, the data sources will be described, and the empirical strategy will be outlined. Lastly, the RDD's results and robustness checks will be presented in addition to the authors' recommendations for future research, for this empirical model can be applied to many public- and private-sector interventions.

2. Context

The COVID-19 global pandemic started to affect the United States in early March 2020. This pandemic shook Americans' daily lives on multiple dimensions. This unexpected event has reaffirmed the differences in beliefs between Democrats and Republicans. Each side of the political spectrum has a preferred method for handling the pandemic. Therefore, Political affiliation might affect the way each state and county handle the pandemic. As a result, democrat and republican counties might have different COVID-19 case rate, death rate and vaccination rate.

Republicans and democrats might have more unobserved different characteristics that pushes them on one side of the political spectrum. To truly assess the causal effect of political affiliation, we need to control for those unobserved characteristics and randomize the political assignment. Regression Discontinuity Design (RDD) is an effective method to achieve this randomization.

Some individuals might argue that county-level political affiliation is not a significantly meaningful treatment to analyze. While that may be true for well-scrutinized outcomes such as COVID-19 case rates, this paper describes a model that can be readily applied to more advanced causal questions. For example, to study the impact of face-covering policies on vaccination rates, a reseacher would need to employ a fuzzy regression discontinuity design. The empirical strategy described in this paper could be utilized for the first stage of such an experiment with minimal changes to the model's design. Therefore, this paper does not exhaust the authors' inquisitiveness around the underlying relationships between politics, policies, and COVID-19. It begins a greater narrative by providing a blueprint for future research.

3. Empirical Strategy

The impact of counties' political affiliation on COVID-19 case, death, and vaccination rates is estimated using a sharp regression discontinuity design (RDD). The running variable is the percentage of Republican votes in the popular vote, and the cutoff is defined as 50% Republican. Therefore, a county with at least 50% Republican votes is classified as treated, and a county with less than 50% Republican votes is classified as untreated. Three different outcomes are specified: case, death, and vaccination rates. The linear specification is as follows:

$$Y_a = \alpha_a + \tau_a D_a + \gamma_a(x - x_{50}) + \delta_a[(x - x_{50})D_a] + \varepsilon_a$$

where Y_a is the outcome, α_a is the intercept, D_a is the dummy variable indicating treatment, x is the running variable, x_{50} centers the running variable to zero at the cutoff, δ_a is the treatment effect, and ε_a is the error term. The quadratic specification is as follows:

$$Y_b = \alpha_b + \tau_b D_b + \gamma_{b1}(x - x_{50}) + \gamma_{b2}(x - x_{50})^2 + \delta_{b1}[(x - x_{50})D_b] + \delta_{b2}[(x - x_{50})^2 D_b] + \varepsilon_b$$

where Y_b is the outcome, α_b is the intercept, D_b is the dummy variable indicating treatment, x is the running variable, x_{50} centers the running variable to zero at the cutoff, δ_{b1} is the treatment effect, and ε_b is the error term. The identification relies on the assumption that county characteristics should be very similar around the cutoff; therefore, counties with a percentage of Republican votes just below the cutoff provide a good counterfactual for counties with a percentage of Republican votes just above the cutoff. Another assumption of an RDD is that observed units have no control over the assignment. An example of gaming in the context of electoral votes could be electoral fraud. If, for example, the republican party can manipulate votes, there could an abnormal number of republican parties immediately at the right of the cutoff. The identification strategy also relies on the assumption that the treatment is strictly enforced passed the cutoff threshold. A candidate with at least 50% votes will necessarily win the elections at the state level.

Imprecise controls are tested for using a density plot and Stata's RD manipulation test using local polynomial density estimation. Figure 1 presents the manipulation testing plot. Counties were grouped into bins of 1% . For example, counties with 45.5% and 45.9% republican votes are put in the same bin. The figure shows that the number of counties is smooth through the cutoff. Therefore, there does not seem to be instances of electoral fraud. To confirm our conclusion from visual inspection, we run a formal RD manipulation test using local polinomial density estimation.

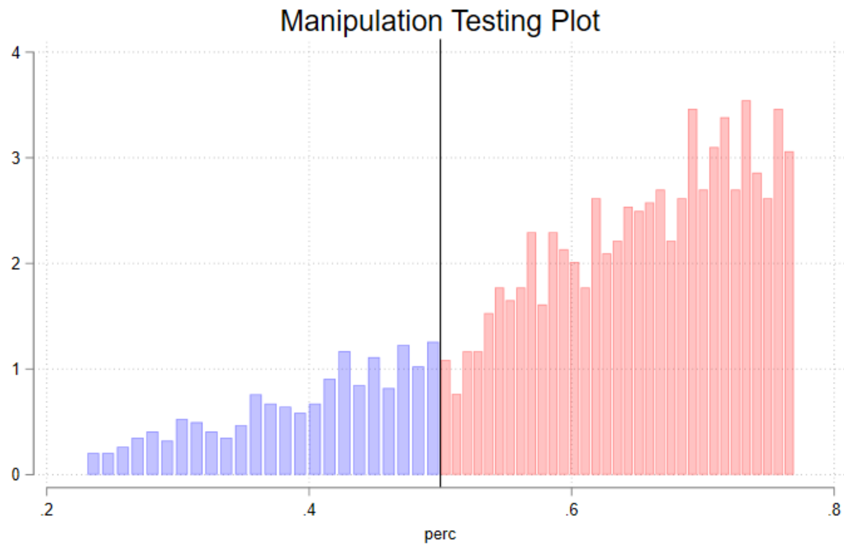

Figure 1. Manipulation testing plot.

Table 1 presents the results of a formal hypothesis testing using local polinomial density estimation. The null hypothsis for the RD manipulation test is that there is no statistically significant difference in the rate of change for the cumulative density function as the cutoff is crossed. The results of the table fail to reject the null hypothesis, indicating that there is not evidence that elections near the cutoff are clustered on either political party. The running variable is valid.

Table 1. RD Manipulation test using local polynomial density estimation.

RD Manipulation test using local polynomial density estimation.

c = 0.500	Left of c	Right of c
Number of obs	586	2451
Eff. Number of obs	286	425
Order est. (p)	2	2
Order bias (q)	3	3
BW est. (h)	0.090	0.090

Number of obs	=	3037
Model	=	unrestricted
BW method	=	comb
Kernel	=	triangular
VCE method	=	jackknife

Running variable: perc.

Method	T	P>|T|
Robust	-1.9588	0.0501

P-values of binomial tests. (H0: prob = .5)

Window Length / 2	<c	>=c	P>|T|
0.003	12	8	0.5034
0.006	24	18	0.4408
0.009	36	29	0.4570
0.012	44	36	0.4340
0.015	55	43	0.2664
0.018	60	52	0.5085
0.021	72	64	0.5485
0.024	85	74	0.4278
0.027	100	80	0.1565
0.030	111	88	0.1186

4. Data

The data was collected from four different sources. Results from the 2016 Presidential election were retrieived from the Massechusetts Institute of Technology's Election Data + Science Lab (MIT Election Data and Science Lab, 2018). The number of COVID-19 cases and deaths were retrieved from the New York Times (New York Times, 2020). The 2020 census data was the retrieved from the US Census Bureau (United States Census Bureau, 2020). The COVID-19 vaccination data was retrieved from the Center for Disease Control and prevention (CDC, 2021). These four sources were combined using the county name as reference.

The first dataset contains the 2016 presidential election results at the county level. The dataset was cleaned by removing the District of Columbia (Washington, D.C.) from the list of states because D.C. is a federal district as opposed to a state. We also restricted the total votes to those toward the Republican party. We added a calculated field for the voting percentage by taking the ratio of candidate votes (Donald Trump) over total votes.

The second dataset from the New York Times contains the COVID-19 cases and deaths. Since the first reported coronavirus case in Washington State on Jan. 21, 2020, The Times has tracked cases of coronavirus in real time as they were identified after testing. Because of the widespread shortage of testing, however, the data is necessarily limited in the picture it presents of the outbreak. Each row of data reports the cumulative number of coronavirus cases and deaths based on their best reporting. The data is the product of dozens of journalists working across several time zones to monitor news conferences, analyze data releases and seek clarification from public officials on how they categorize cases. For each date, they show the cumulative number of confirmed cases and deaths as reported that day in that county. All cases and deaths are counted on the date they are first announced.

We are aware that each county experienced outbreaks at different times, and the COVID-19 vaccine also impacted those numbers. To account for those facts, we restricted the dataset to November 16, 2020, a date by which the counties would have experienced their outbreaks and before the vaccine was available. In addition, each county has a different population; therefore, the flat total number of COVID-19 cases and deaths depends on the population in that county. To account for the population differences, we used a third dataset from the US Census Bureau containing the 2020 census population estimates at the county level. We created a calculated field for COVID-19 case and death rates by using the 2020 population estimates.

The fourth dataset contains the COVID-19 vaccination data at the county level. The CDC is using both new and existing information technology (IT) systems to rapidly collect reliable data about how many doses of COVID-19 vaccines have been delivered (distribution) and how many people have been vaccinated with those doses (administration). CDC uses the IZ Data Lake to receive, store, manage, and analyze COVID-19 vaccine distribution and administration data from all sources, including jurisdictions, pharmacies, and federal entities, which use various reporting methods, including immunization information systems, Vaccine Administration Management System, and direct data submission.

On April 19, White House COVID-19 Response Team announced that all adults are eligible for the COVID-19 vaccine (White House). Therefore, we filtered our data to May 31, 2021. We assumed that by that time, the adults who approve the vaccine would have enough time to get their doses and be completely vaccinated. We used the percent of people 18+ who are fully vaccinated (have second dose of a two-dose vaccine or one dose of a single-dose vaccine) based on the jurisdiction and county where recipient lives.

5. Results and Robustness Checks

Table 2 presents the results of three specifications with COVID-19 case rate as the dependent variable. The first specification is a simple linear regression on COVID-19 case rate and the percentage of Repuplican votes in the county. When we don't control for the differences in slopes at the left and right sides of the cutoff, being republican has a significant negative effect on the number of cases. It shows that counties with a higher number of republican votes tends to have a lower number of COVID-19 cases. However, this regression is a simple correlation not a causation since the sample is not truly randomized.

The second specification is a RD regression with linear slope controls on the left and right side of the cutoff. This specification can assess the impact effect of political affiliation if any since the counties around the cutoff are very similar except from their political affiliations. Being Republican at the cutoff does not have a significant effect on the COVID-19 cases. The significant positive coefficient of the intetraction between being republican and the percentage of republican votes show that the slope of the line at the right side of the cutoff is more shallow than the one on the left.

The third specification is a RD regression with quadratic slope controls on the left and right side of the cutoff. Similarly to the previous regression, being Republican at the cutoff does not have a significant effect on the COVID-19 cases. The significant positive coefficient of the intetraction between being republican and the squre of the percentage of republican votes show that the slope of the curve at the right side of the cutoff is significantly different from the one on the left.

Table 2. Regression results for COVID-19 case rates. (1) Linear fit with the same slope. (2) Linear fit with different slopes. (3) Quadratic fit.

	(1) Case Rate	(2) Case Rate	(3) Case Rate
Treatment	-0.00490*	-0.000694	0.00376
	(0.00237)	(0.00172)	(0.00303)
% Republican Linear	-0.0310***	-0.0962*	-0.321*
	(0.00888)	(0.0397)	(0.129)
Treatment x % Rep.		0.0845*	0.441*
		(0.0411)	(0.179)
% Rep. Quadratic			-0.707*
			(0.297)
Treat x % Rep. Sqrd.			1.064*
			(0.503)
Constant	0.0472***	0.0394***	0.0289***
	(0.00334)	(0.00158)	(0.00477)
Observations	3037	3037	3037
R-squared	0.116	0.120	0.125
Adjusted R-squared	0.101	0.105	0.109

Standard errors in parentheses
* p<0.05, ** p<0.01, *** p<0.001

Figures 2 and 3 are the graphic represntations of the specification (2) and (3). As shown in those figures, there is no discontinuity around the cutoff. However, it clearly shows that counties on the left and right sides of the cutoff have a different relation with the COVID-19 case rate. On the one hand, Democratic counties seem to have less COVID-19 cases as they become more Republican. On the other hand, Republican counties seem to have a constant COVID-19 case rate; Republican states with more than 80% of Republican votes tend to have less cases as they gain more votes. This could be explained by the fact that democratic states tend to be smaller and more congested than Republican states. Therefore, people are more likely to be infected because there are more people per square mile.

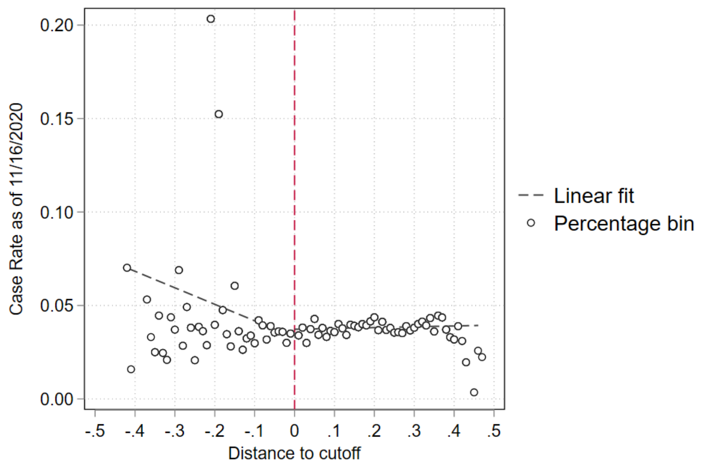

Figure 2. Regression discontinuity plot for regression (2) from Table 2.

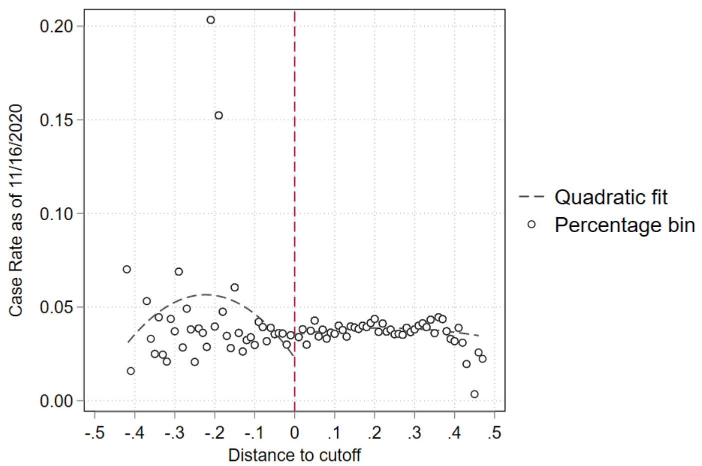

Figure 3. Regression discontinuity plot for regression (3) from Table 2.

Table 3 presents the results of three specifications with COVID-19 death rate as the dependent variable. The first specification is a simple linear regression on COVID-19 death rate and the percentage of Republican votes in the county. When we don't control for the differences in slopes at the left and right sides of the cutoff, being republican has a significant negative effect on the number of deaths. The regression shows that counties with a higher number of republican votes tends to have a lower number of COVID-19 related deaths. However, this regression is once again a simple correlation not a causation since the sample is not truly randomized.

The second specification is a RD regression with linear slope controls on the left and right side of the cutoff. This specification can assess the impact effect of political affiliation if any since the counties around the cutoff are very similar except from their political affiliations. The specification shows that being Republican at the cutoff does not have a significant effect on the number of COVID-19 related deaths. The significant positive coefficient of the interaction between being republican and the percentage of republican votes show that the slope of the line at the right side of the cutoff is shallower than the one on the left.

The third specification is a RD regression with quadratic slope controls on the left and right side of the cutoff. Similarly to the previous regression, being Republican at the cutoff does not have a significant effect on the COVID-19 related deaths. The significant positive coefficient of the interaction between being republican and the square of the percentage of republican votes show that the slope of the curve at the right side of the cutoff is significantly different from the one on the left.

Table 3. Regression results for COVID-19 death rates. (1) Linear fit with the same slope. (2) Linear fit with different slopes. (3) Quadratic fit.

	(1) Death Rate	(2) Death Rate	(3) Death Rate
Treatment	-0.000179**	-0.0000597	0.0000134
	(0.0000623)	(0.0000538)	(0.0000803)
% Republican Linear	-0.000715**	-0.00257**	-0.00690*
	(0.000226)	(0.000945)	(0.00300)
Treatment x % Rep.		0.00240*	0.00942*
		(0.000982)	(0.00416)
% Rep. Quadratic			-0.0136*
			(0.00696)
Treat x % Rep. Sqrd.			0.0195
			(0.0119)
Constant	0.000949***	0.000725***	0.000523***
	(0.0000798)	(0.0000516)	(0.000117)
Observations	3037	3037	3037
R-squared	0.119	0.124	0.127
Adjusted R-squared	0.104	0.109	0.112

Standard errors in parentheses
* p<0.05, ** p<0.01, *** p<0.001

Figures 4 and 5 are the graphic represntations of the specification (2) and (3). As shown in those figures, there is no discontinuity around the cutoff. However, it clearly shows that counties on the left and right sides of the cutoff have a different relation with the COVID-19 death rate. On the one hand, Democratic counties seem to have less COVID-19 related deaths as they become more Republican. On the other hand, Republican counties seem to have a constant COVID-19 death rate; Republican states with more than 80% of Republican votes tend to have less COVID-19 related deaths as they gain more votes. This could also be explained by the fact that Democratic states tend to be smaller and more congested than Republican states. Since people in Republican counties are less likely to be infected, they are, as a result less likely to die from COVID-19.

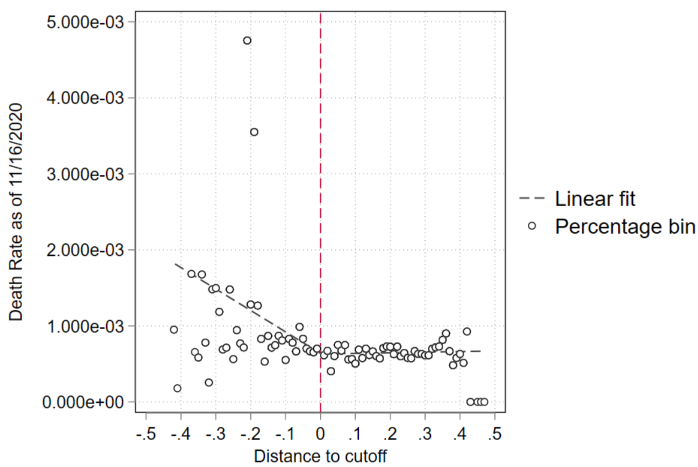

Figure 4. Regression discontinuity plot for regression (2) from Table 3.

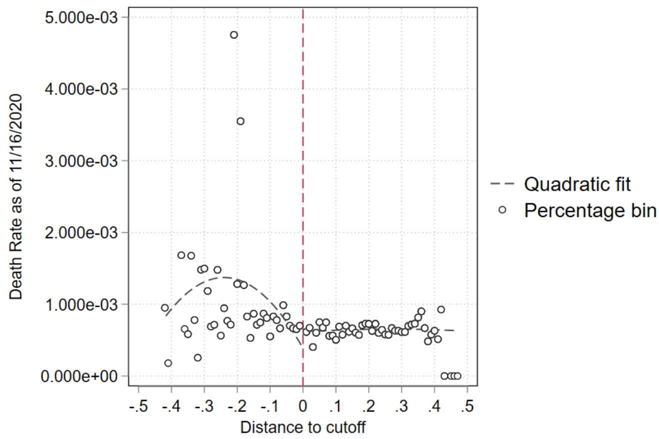

Figure 5. Regression discontinuity plot for regression (3) from Table 3.

Table 4 presents the results of three specifications with COVID-19 adult vaccination rate as the dependent variable. The first specification is a simple linear regression on the COVID-19 adult vaccination rate and the percentage of Republican votes in the county. When we don't control for the differences in slopes at the left and right sides of the cutoff, being republican has does not have a significant negative effect on the number of vaccinations. The regression also shows that counties with a higher number of republican votes tends to have a lower number of COVID-19 adult vaccinations. However, this linear regression is once again a simple correlation not a causation since the sample is not truly randomized.

The second specification is a RD regression with linear slope controls on the left and right side of the cutoff. Being Republican at the cutoff does not have a significant effect on the number of COVID-19 related deaths. The significant negative coefficient of the interaction between being republican and the percentage of republican votes show that the slope of the line at the right side of the cutoff is steeper than the one on the left.

The third specification is a RD regression with quadratic slope controls on the left and right side of the cutoff. As in the previous regression, being Republican at the cutoff does not have a significant effect on the COVID-19 related deaths. The coefficients of the added squared variables are not significant. Therefore, the linear fit on both sides is more accurate than a quadratic fit in this regression.

Interestingly, the each of those specifications had a high predictive power with a R-squared of 0.76. This means that our specification can explain 76% of the variation in adult vaccination rate.

Table 4. Regression results for COVID-19 vaccination rates. (1) Linear fit with the same slope. (2) Linear fit with different slopes. (3) Quadratic fit.

	(1)	(2)	(3)
	Vax Rate 18+	Vax Rate 18+	Vax Rate 18+
Treatment	0.0132	0.00644	0.00764
	(0.00749)	(0.00838)	(0.00950)
% Republican Linear	-0.312***	-0.207***	-0.262
	(0.0213)	(0.0590)	(0.154)
Treatment x % Rep.		-0.135*	-0.0501
		(0.0636)	(0.239)
% Rep. Quadratic			-0.172
			(0.484)
Treat x % Rep. Sqrd.			0.268
			(0.825)
Constant	0.384***	0.396***	0.394***
	(0.00494)	(0.00743)	(0.00931)
Observations	3037	3037	3037
R-squared	0.762	0.763	0.763
Adjusted R-squared	0.758	0.759	0.759

Standard errors in parentheses
* p<0.05, ** p<0.01, *** p<0.001

Figures 6 and 7 are the graphic represntations of the specification (2) and (3). As shown in those figures, there is no discontinuity around the cutoff. However, it clearly shows that counties on the left and right sides of the cutoff have a different relation with the COVID-19 adult vaccination rate. On the one hand, Democrat counties seem to have less COVID-19 cases as they become more Republicans. On the other hand, Republican counties seem to have a decreasing number of adult COVID-19 vaccinations the more republican votes they have. This could be explained by the fact that Republican states tend to have less COVID-19 cases and deaths than their Democrat counterparts.

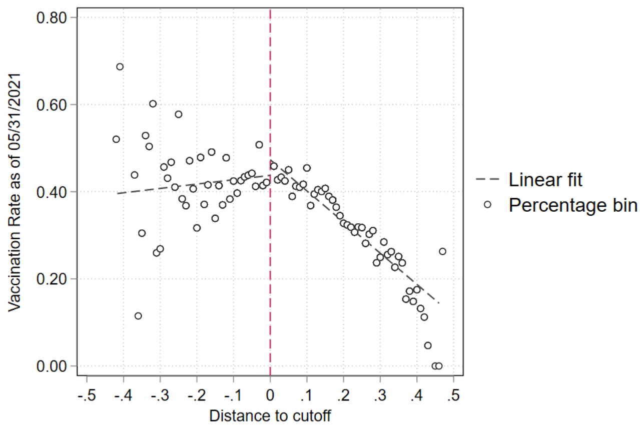

Figure 6. Regression discontinuity plot for regression (2) from Table 4.

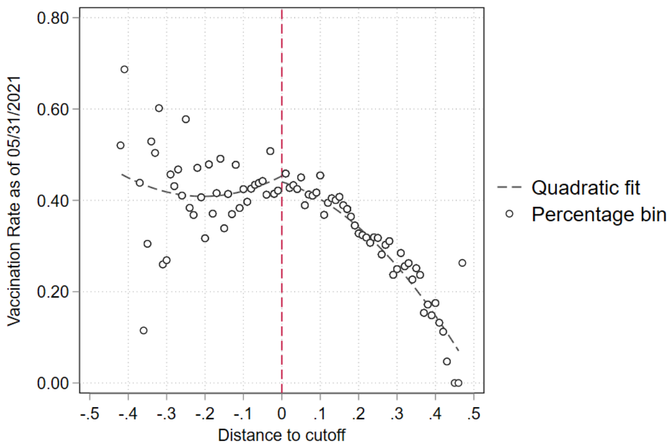

Figure 7. Regression discontinuity plot for regression (3) from Table 4.

A RDD only examines the effect of the treatment at the cutoff. Therefore, as we reduce the bandwidth of our running variable around the cutoff, the results of the specifications should fluctuate a lot. To test, this assumption, the did additional regressions with a reduced bandwidth of 40%, 30%, 20% and 10% around the cutoff. Tables 5, 6, 7, 8, 9 and 10 in the appendix show the results of the specifications with reduced bandwidth. As expected, being republican at the cutoff, did not have a significant effect on the COVID-19 case rate, death rate and adult vaccination rate.

6. Conclusion and Recommendations for Future Work

This study reveals that political affiliation, in and of itself, has no significant impact on the county-level outcomes of COVID-19 case rate, death rate, and vaccination rate. From the figures shown in this paper's results, it is clear that there are different trends across Republican counties when compared to Democratic counties. However, at the cutoff where counties are "just Republican" or "just Democrat," there is no significant change in outcome. Several modifications can be made to this regression discontinuity model to potentially improve the results and test for robustness. First, additional covariates can be included to increase the data's level of explainability. One example is the addition of weather data to help explain case-rate variations in different regions of the country. Second, this paper analyses COVID-19 data from the New York Times. To test for robustness, the model could be replicated with an alternative data source such as Johns Hopkins University. Lastly, the empirical strategy described in this paper could be utilized for the first stage of a study that explores the impact of face-covering policies on vaccination rates. This paper does not exhaust the authors' inquisitiveness around the underlying relationships between politics, policies, and COVID-19. As previously mentioned, this paper begins a greater narrative by providing a blueprint for future research.

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Appendix

Table 5. Bandwidth robustness test for case rates, linear fit.

Case Rates Across Multiple Bandwidths - Linear Fit

	(1) +-40%	(2) +-30%	(3) +-20%	(4) +-10%
Treatment	-0.000554 (0.00178)	0.00464 (0.00295)	0.00733 (0.00614)	0.00216 (0.00200)
Observations	3020	2662	1705	792

Standard errors in parentheses
* p<0.05, ** p<0.01, *** p<0.001

Table 6. Bandwidth robustness test for case rates, quadratic fit.

Case Rates Across Multiple Bandwidths - Quadratic Fit

	(1) +-40%	(2) +-30%	(3) +-20%	(4) +-10%
Treatment	0.00506 (0.00324)	0.00443 (0.00363)	-0.00226 (0.00319)	0.00217 (0.00254)
Observations	3020	2662	1705	792

Standard errors in parentheses
* p<0.05, ** p<0.01, *** p<0.001

Table 7. Bandwidth robustness test for death rates, linear fit.

Death Rates Across Multiple Bandwidths - Linear Fit

	(1) +-40%	(2) +-30%	(3) +-20%	(4) +-10%
Treatment	-0.0000561 (0.0000550)	0.0000525 (0.0000780)	0.000124 (0.000147)	-0.0000430 (0.0000704)
Observations	3020	2662	1705	792

Standard errors in parentheses
* p<0.05, ** p<0.01, *** p<0.001

Table 8. Bandwidth robustness test for death rates, quadratic fit.

Death Rates Across Multiple Bandwidths - Quadratic Fit

	(1) +-40%	(2) +-30%	(3) +-20%	(4) +-10%
Treatment	0.0000524 (0.0000846)	0.0000372 (0.0000933)	-0.000149 (0.0000888)	0.0000309 (0.0000956)
Observations	3020	2662	1705	792

Standard errors in parentheses
* p<0.05, ** p<0.01, *** p<0.001

Table 9. Bandwidth robustness test for vaccination rates, linear fit.

Vaccination Rates Across Multiple Bandwidths - Linear Fit

	(1) +-40%	(2) +-30%	(3) +-20%	(4) +-10%
Treatment	0.00610	0.00754	0.00725	-0.0113
	(0.00845)	(0.00894)	(0.0104)	(0.0152)
Observations	3020	2662	1705	792

Standard errors in parentheses
* p<0.05, ** p<0.01, *** p<0.001

Table 10. Bandwidth robustness test for vaccination rates, quadratic fit.

Vaccination Rates Across Multiple Bandwidths - Quadratic Fit

	(1) +-40%	(2) +-30%	(3) +-20%	(4) +-10%
Treatment	0.00824	0.0111	0.00152	-0.00295
	(0.00960)	(0.0106)	(0.0130)	(0.0196)
Observations	3020	2662	1705	792

Standard errors in parentheses
* p<0.05, ** p<0.01, *** p<0.001